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The symmetric and asymmetric effects of climate change on rice productivity in Malaysia

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ABSTRACT

The current study aims to examine the symmetric and asymmetric effects of climate change (CC) on rice productivity (RP) in Malaysia. The Autoregressive-Distributed Lag (ARDL) and Non-linear Autoregressive Distributed Lag (NARDL) models were employed in this study. Time series data from 1980 to 2019 were collected from the World Bank and the Department of Statistics, Malaysia. The estimated results are also validated using Fully Modified Ordinary Least Squares (FMOLS), Dynamic Ordinary Least Squares (DOLS), and Canonical Cointegration Regression (CCR). The findings of symmetric ARDL show that rainfall and cultivated area have significant and advantageous effects on rice output. The NARDL-bound test outcomes display that climate change has an asymmetrical long-run impact on rice productivity. Climate change has had varying degrees of positive and negative impacts on rice productivity in Malaysia. Positive changes in temperature and rainfall have a substantial and destructive impact on RP. At the same time, negative variations in temperature and rainfall have a substantial and positive impact on rice production in the Malaysian agriculture sector. Changes in cultivated areas, both positive and negative, have a long-term optimistic impact on rice output. Additionally, we discovered that only temperature affects rice output in both directions. Malaysian policymakers must understand the symmetric and asymmetric effects of CC on RP and agricultural policies that will promote sustainable agricultural development and food security.

1. Introduction

Agriculture productivity is significantly impacted by climate change. Changes in worldwide temperature have had an enormous

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effect on the agriculture industry because many crops are temperature sensitive. Climate change is putting strain on agricultural operations [35] by increasing temperature, altering patterns of precipitation, and emergent variability of rainfall during the summer monsoon season [1,3,11,52,60,61]. Global CC has become a severe menace to agricultural production and is essential to the long-term development of any country [4]. Although underdeveloped countries are more severely impacted by climate change than developed ones [38], this is due to their greater vulnerability to the phenomenon and limited capacity to manage its consequences [10]. Changes to the global rainfall, temperature, and CO_2 regimes will probably have a considerable impact on agricultural production as Earth's climate is changing quickly [31]. Changes in global temperature, rainfall, and carbon emissions contribute to CC, which has an ongoing impact on agricultural development and productivity [15,30]. Due to the primary causes of CC, such as increased precipitation and warmer weather, agricultural productivity has been declining [26]. Small and medium farmers are especially vulnerable to climate change since it negatively influences agricultural output, and their income primarily depends on agriculture and related industries [67].

In developing countries, agriculture remains the primary source of income, and it forms the foundation of the South Asian economy. With just 5% of the world's agricultural land, South Asia provides food for 20% of the global population. Given that 70% of South Asia's population lives in villages and that cultivation is the key resource of income for this enormous section of the population, it is possible to evaluate the significance of agriculture in this region [16]. There is an expectation that CC will impact crop yield, particularly rice, because agriculture differs in climate phases and weather conditions. For example, a 4% upsurge in temperature compared to pre-industrial levels will raise the likelihood of hot spells harming rice and maize crops by 27 to 46% and 5 to 50%, respectively [6,57].

High temperatures limit the ability to produce rice in tropical nations like Malaysia [18,40,57]. Additionally, fluctuation in precipitation, particularly in low-altitude areas, is a significant factor that may impact the output of rain-fed rice [32,41], such as those located in Malaysia [23,57]. Malaysia's agricultural industry has major obstacles as a developing nation. The lowest and highest temperatures in granary areas rise by 0.3–0.5 °C and 0.2–0.3 °C, respectively, per span, according to Firdaus et al. [19]. This will result in lower rice yields, which will impair Malaysia's capacity to achieve food security. Rice and other agricultural crop yields are declining due to climate change, according to Firdaus [23], Tang [57], and Vaghefi et al. [61]. CC has a disastrous impact on crop yield and foodstuff, and nutrition security in emerging nations. Combating environmental transformation and its impacts on farming production is challenging because of the complex relationship between crop production and climatic change. Agriculture is also negatively impacted by CC, particularly at low latitudes and in tropical regions [24,51,57]. It is critical to determine how climate change can impact Malaysian rice production, given that a continuous rise in temperature is projected [47]. Several studies, such as [20,27,65], only in Malaysia have used a symmetric association between rice production and CC. However, there is a dearth of literature in the existing body of knowledge concerning symmetrical and asymmetrical dynamic interactions between climatic changes and RP in Malaysia. Therefore, this study examines the symmetric and asymmetric effects of CC on rice productivity in Malaysia. The ARDL and NARDL models were employed in this study, which utilised time series data from 1980 to 2019. Except for the introduction, the remaining work is designed as follows: The literature review is covered in Part 2, the methodology for the current study is presented in Section 3, the empirical findings and analysis are discussed in Section 4, the discussion and policy implications are deliberated in Section 5, and the manuscript's conclusion is presented in Section 6.

2. Literature review

Food availability is also an additional concern that should worry all humans, and the effect of CC on crop production has drawn a lot of interest. Agriculture is thought to be the sector most sensitive to global CC [18]. Numerous research projects have been done on the connection between global CC and agricultural output, and environmentalists and researchers are increasingly in agreement that there is a bad association between global CC and agricultural productivity in emerging countries [9]. Agriculture production and climate change are strongly correlated [5]. Climate change impacts crop cultivation output sub-sectors, such as cereals, dairy, fishing, and forestry [10a,10b]. The prolonged periods of rain could have a negative effect on agricultural productivity. Rahman et al. [48] note that rainfall has changed in Bangladesh during the monsoon season with an increasing tendency, having a substantial impact on the rainfed rice crop (aman). This is another example of the effect of weather change. The impact of meteorological factors like temperature and rainfall on grain cultivation in Tunisia was studied by Attiaoui and Boufateh [7]. They discovered that precipitation significantly impacts cereal farming in Tunisia, whereas temperature significantly impacts cereal production but with less elasticity. Sub-Saharan African countries' agricultural output is decreased by climate change, as shown by Warsame et al. [64]. He discovered that rainfall considerably boosts agricultural output in Sub-Saharan African nations. The difference between local supply and demand in Malaysia is expected to widen as a result of climate change's impact on rice productivity. It has been established that rising temperatures are more detrimental to paddy output than changes in rainfall. Current paddy output could decrease by 0.12% with a 1% increase in rainfall but by 3.44% with a 1% upsurge in temperature [58].

Rice is a staple diet for more than 50% of the world's population [62]. Crop productivity is highly impacted by climate elements such as temperature (TEM) and rainfall (RNF) [1, 46]. CC-related fluctuations in temperature and precipitation patterns impact the growth phases of crops, including rice [46,57]. Variations in TEM and RNF negatively affect the phases of rice growth, ensuing in less rice being produced. Crop output declines are caused mainly by shorter growth phases, increased heat stress during the crucial reproductive phase, reduced solar capacity, increased respiratory processes, and increased rice water requirements [1,46,60]. However, high temperatures are harmful to rice development and, therefore, necessary for rice yield. The highest TEM has a negative impact on rice plants throughout their reproductive period, resulting in a shorter rice crop time and a poorer rice yield. As an illustration, a 4% rise in TEM above pre-industrial levels will upsurge the risk that hot periods will impair rice and maize harvests by 27 to

46% and 5 to 50%, respectively [6,57]. By 2030, it is anticipated that the production of rice in Brazil, Central America, and Southeast Asia will decrease by up to 5% [34].

Future changes in temperature, carbon dioxide levels, and rainfall brought on by global warming are anticipated to have an impact on rice output. Rapid climate change implications include the adverse effects of intense weather on the systems used to produce rice and the availability of food [17]. Previous research demonstrates that CC is causing a rise in TEM while also having negative effects on rice crops, which will ultimately reduce agricultural efficiency and condition. According to research by Janjua et al. [29], Pakistan's wheat production is positively impacted by CC parameters, for example, carbon emissions, average temperature, and average precipitation in both the long and short term. According to Zaied and Cheikh [66], yearly high temperatures reduce both date and cereal production, whereas annual rainfall increases cereal production in Tunisia. In a country with limited water resources, increased temperatures linked to climate change have been proven to negatively influence output through their adverse effects on fodder [18].

High temperatures limit the ability to produce rice in tropical nations like Malaysia [8,28]. Rain-fed rice production could be negatively impacted by the unpredictable amount and distribution of precipitation, especially in low-altitude areas like Malaysia [23,39,57]. A study in Northwest Selangor, Malaysia, highlighted the location-specific effects of CC while identifying the detrimental effects of TEM and RNF variations on rice production [57]. However, the effects of increased CO_2 and warmth in California, United States, caused a 16% yield decline in the rice variety [37]. Rice yield in Southwestern China would decline by up to 10.5% by 2050 and 47.9% by 2080 as a result of higher temperature and CO_2 (at 700 ppm) [63]. The majority of people on Earth consume rice as part of their daily diet, which numbers over 3 billion people [9,69]. Asia is the region where 90% of the world's rice is produced and consumed [70]. Kumar et al. [26] discovered that a large land area dedicated to cereal farming increases cereal crop yield in India. A staple food in Malaysia is rice. Peninsular Malaysia accounts for 85.5% of all paddy production in Malaysia [23,71]. Eight large paddy granary sites can be thought of as Malaysia's "rice bowl" and source of food security [72]. Agricultural productivity is positively impacted by the area of arable land over the long run, but negatively in the short run in Malaysia [9,55,73].

3. Methodology

3.1. Variables and data

This study used yearly time series data for Malaysia from 1980 to 2019. The primary data sources were the World Development Indicators (WDI) databases and the Malaysian Department of Statistics (DOSM). Rice production (RP), cultivated area (CA), rainfall (RNF), and temperature (TEM) are the variables of interest (Table 1).

This study looks at the symmetric and asymmetric associations among rice production, cultivated area, rainfall, and temperature in Malaysia. With the exception of temperature, we used the following model to convert all data series to natural logarithms. To obtain accurate estimations and normalise the data, all the variables are converted into natural logarithms [39] except temperature.

$$LRP_t = \beta_0 + \beta_1 LCA_t + \beta_2 LRNF_t + \beta_3 TEM_t + \varepsilon_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

To test for asymmetric effects, cultivated area, rainfall, and temperature are split into positive and negative changes (LCA+, LCA-, LRNF+, LRNF-, and TEM+, TEM-). The modified model is depicted below.

$$LRP_t = \beta_0 + \beta_1 LCA_t^+ + \beta_2 LCA_t^- + \beta_3 LRNF_t^+ + \beta_4 LRNF_t^- + \beta_5 TEM_t^+ + \beta_6 TEM_t^- + \varepsilon_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (2)$$

3.2. Methodology of econometrics

Before using cointegration and causality techniques, a thorough unit root analysis must be performed as a first step. We move on to linear and non-linear cointegration and long-run analysis after forming that the variable integration level satisfies the fundamental criteria of the methods, namely, that the series are stationary at I (1) or/and I (0) or combined with both. We used ARDL approaches that were both symmetric and asymmetric. Variables can be incorporated at either I (0) or I (1) using the asymmetric and symmetric ARDL approaches, which are both extremely versatile. These techniques work well with lesser samples. An acceptable lag duration can address the potential endogeneity issue in the ARDL, which calls for the selection of an appropriate lag. Similar to how it effectively addresses the problem of potential multicollinearity in the non-linear ARDL, a suitable lag length [54]. The ARDL technique simultaneously delivers short- and long-term outcomes, whereas the lagged ECT provides details on converging to long-run stability. The following equation (1.1) is transformed into the below-displayed ARDL model.

Table 1
Data source and variables.

Variables	Sign	Description	Sources of information
Rice production	RP	Rice production in metric ton	DOSM
Cultivated area	CA	Cultivated area in hectare	DOSM
Rainfall	RNF	Annual average rainfall in millimeter	WDI
Temperature	TEM	Annual mean temperature in Celsius	WDI

$$\Delta LRP_t = \beta_0 + \beta_1 LRP_{t-1} + \beta_2 LCA_{t-1} + \beta_3 LRNF_{t-1} + \beta_4 TEM_{t-1} + \sum_{i=1}^{q} \delta_1 \Delta LRP_{t-i} + \sum_{j=1}^{q} \delta_2 \Delta LCA_{t-i} + \sum_{l=1}^{q} \delta_3 \Delta LRNF_{t-i} + \sum_{m=1}^{q} \delta_4 \Delta TEM_{i-1} + \mu_t \dots\dots\dots\dots \tag{1.1}$$

Where Δ denotes the initial variation, the drift component is represented by β_0, the time trend by t, the optimal lag length by q, and the typical white noise residuals by μ_t.

3.3. Estimation method

To evaluate whether there are long-term connection dynamics between variables, we first utilised an OLS technique to estimate Equation (1), and then we employed a Wald test and an F-test to determine mutual consequence for the coefficients of lagged variables. (LRP (LRP|LCA, LRNF, TEM) denotes the null hypothesis that no long-term association exists. As a result, the null hypothesis posits that the variables are uncorrelated, (H_0): $\delta 1 = \delta 2 = \delta 3 = \delta 4 = 0$, whereas the alternative hypothesis (H_1) is: $\delta 1 \neq \delta 2 \neq \delta 3 \neq \delta 4 \neq 0$. The significance level (top and bottom bounds) put out by Pesaran, Shin, and Smith [43] is then compared to the F test. In order to estimate the long-term coefficient of the ARDL model (Equation (1.2)), the co-integration connection between the variables must first be established.

$$LRP_t = \beta_{0+} \sum_{i=1}^{q} \delta_1 LRP_{t-i} + \sum_{j=1}^{q} \delta_2 LCA_{t-i} + \sum_{l=1}^{q} \delta_3 LRNF_{t-i} + \sum_{m=1}^{q} \delta_4 \ TEM_{t-i} + \varepsilon t \dots\dots\dots\dots \tag{1.2}$$

Using this method, we selected the appropriate lag duration in the ARDL model using Akaike information criterion (AIC) criterion. Lastly, as shown below, we estimate the short-run models, where θi signifies the long-run balance speed of adjustment after the shock in the short-run (Equation (1.3)) relations with the model of error correction (ECM).

$$\Delta LRPt = \beta_{0+} \sum_{i=1}^{q} \delta_1 \Delta LRP_{t-i} + \sum_{j=1}^{q} \delta_2 \Delta LCA_{t-i} + \sum_{l=1}^{q} \delta_3 \Delta LRNF_{t-i} + \sum_{m=1}^{q} \delta_4 \ \Delta TEM_{t-i} + \theta_i ECT_{t-1} + \varepsilon t \tag{1.3}$$

3.4. Non-linear ARDL method

The asymmetric component is ignored by ARDL, which analyses long and short run cointegration. Following Shin et al. [54] methodology, we applied NARDL to identify the unequal association among the study variables. The negative and positive changes in cultivated area (LCA+, LCA-), rainfall (LRNF+, LRNF-), and temperature (TEM+, TEM-) are already shown in Equation (2). The cumulative total of both positive and negative changes is defined as follows from equations (2a) to (2f).

$$LCA_t^+ = \sum_{i=1}^{t} \Delta LCA_i^+ = \sum_{i=1}^{t} Max(\Delta LCA_i, 0) \dots\dots\dots\dots \tag{2a}$$

$$LCA_t^- = \sum_{i=1}^{t} \Delta LCA_i^- = \sum_{i=1}^{t} Min(\Delta LCA_i, 0) \dots\dots\dots\dots \tag{2b}$$

$$LRNF_t^+ = \sum_{i=1}^{t} \Delta LRNF_i^+ = \sum_{i=1}^{t} Max(\Delta LRNF_i, 0) \dots\dots\dots\dots \tag{2c}$$

$$LRNF_t^- = \sum_{i=1}^{t} \Delta LRNF_i^- = \sum_{i=1}^{t} Min(\Delta LRNF_i, 0) \dots\dots\dots\dots \tag{2d}$$

$$TEM_t^+ = \sum_{i=1}^{t} \Delta TEM_i^+ = \sum_{i=1}^{t} Max(\Delta TEM_i, 0) \dots\dots\dots\dots \tag{2e}$$

$$TEM_t^- = \sum_{i=1}^{t} \Delta TEM_i^- = \sum_{i=1}^{t} Min(\Delta TEM_i, 0) \dots\dots\dots\dots \tag{2f}$$

After that, we constructed the NARDL model with the Shin et al. (2014)

$$\Delta LRP_t = \varphi_0 + \lambda_1 LRP_{t-1} + \lambda_2^+ LCA_{t-1}^+ + \lambda_3^- LCA_{t-1}^- + \lambda_4^+ LRNF_{t-1}^+ + \lambda_5^- LRNF_{t-1}^- + \lambda_6^+ TEM_{t-1}^+ + \lambda_7^- TEM_{t-1}^- + \sum_{i=1}^{q} \varphi_i \Delta LCO2_{t-i}$$
$$+ \sum_{i}^{q} (\varphi_i^+ \Delta LCA_{t-i}^+ + \varphi_i^- \Delta LCA_{t-i}^- + \sum_{i}^{q} (\varphi_i^+ \Delta LRNF_{t-i}^+ + \varphi_i^- \Delta LRNF_{t-i}^-) + \sum_{i}^{q} (\varphi_i^+ \Delta TEM_{t-i}^+ + \varphi_i^- \Delta TEM_{t-i}^-) + +\mu_t \quad (3)$$

Where, $\sum_i^q \varphi_i^+$ and $\sum_i^q \varphi_i^-$ capture the short-run positive and negative effects of cultivated area, precipitation, and temperature on rice production, whereas λ_i^+ and λ_i^- captures the long-run effect of cultivated area, rainfall, and temperature on rice production. The error correction model is shown below:

$$\Delta LRP_t = \sum_{i=1}^{q} \varphi_i \Delta LRP_{t-i} + \sum_{i}^{q} (\varphi_i^+ \Delta LCA_{t-i}^+ + \varphi_i^- \Delta LCA_{t-i}^- + \sum_{i}^{q} (\varphi_i^+ \Delta LRNF_{t-i}^+ + \varphi_i^- \Delta LRNF_{t-i}^-)$$
$$+ \sum_{i}^{q} (\varphi_i^+ \Delta TEM_{t-i}^+ + \varphi_i^- \Delta TEM_{t-i}^-) + \theta_i ECT_{t-1} + \mu_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (4)$$

The error correction term, represented by θi in (4), also illustrates the rate of adjustment of the long-run balance following the short-run shock. The short-run coefficients are represented by φi, while the short-run adjustment asymmetries are represented by φ_i^+ and φ_i^-.

In order to determine whether there is a cointegration relationship, the bound test employs the F statistic for a mutual significance test, according to Pesaran et al. [43] and the usual Wald test is used to look at short-run (φ = φ+ = φ−) and long-run (λ = λ+ = λ−) asymmetry for CA, RNF, and TEM. The dynamic multiplier effect is assessed after validating the long-run connection, and a 1% variation in LCA_{t-1}^+, LCA_{t-1}^-, , $LRNF_{t-1}^+$, $LRNF_{t-1}^-$, TEM_{t-1}^+, *and* TEM_{t-1}^-, $LTIN_{t-1}^+$, may be obtained from Eq (3).

$$\alpha_1 = -\frac{\lambda_2}{\lambda_1}, \alpha_2 = -\frac{\lambda_3}{\lambda_1}, \alpha_3 = -\frac{\lambda_4}{\lambda_1}, \alpha_4 = -\frac{\lambda_5}{\lambda_1}, \alpha_5 = -\frac{\lambda_6}{\lambda_1}, \alpha_6 = -\frac{\lambda_7}{\lambda_1} \quad (5)$$

It is possible to see system shocks, with dynamic adjustment away from and toward the stability level, based on the predicted dynamic multipliers in equation 5.

3.5. Model diagnostic and stability testing

Several diagnostic tests were performed to assess the model's reliability, as suggested by Pesaran B and Pesaran M [44]. Among the diagnostic tests used were normality, serial correlation, heteroscedasticity (ARCH), and the Ramsey RESET test. Additionally, we ran the Brown, Durbin, and Evans (1975) stability tests, which rely on multiplier effects and recursive regression residuals, known as the cumulative sum (CUSUM) and cumulative sum of squares (CUSUMSQ). We also looked at the multiplier impacts on the research variables.

4. Empirical results and analysis

4.1. Descriptive statistics

Before beginning any regression analysis, it is critical to investigate the inherent characteristics of the variables as well as the relationships between them. Temperature output has the highest average value (25.629), while rainfall has the lowest average value (8.036), according to the statistical analysis provided in Table 2. All of the variables perform well because their standard deviations are lower than their average values. Thus, the variables can be used to estimate. The trend of endogenous variables is depicted in Fig. 1.

4.2. Non-linearity and stationary testing

Time series-dependent regression analysis makes the assumption that the underlying time series data are stationary. Serial correlation between succeeding data in many macroeconomic time series, especially those with very tiny sampling intervals, shows non-stationarity. This indicates that the traditional T and F-tests are inappropriate for the analysis. In addition, the study may suffer from (i) unauthentic regression, which has a larger R^2 value and a low Durbin-Watson statistic value [25,45] and (ii) irregular and less ordered

Table 2
Descriptive statistics for the variables under consideration.

	RP	CA	RNF	TEM
Mean	13.788	12.828	8.036	25.629
Maximum	14.164	12.962	8.280	26.300
Minimum	13.240	12.517	7.837	24.960
Std. Dev.	0.210	0.098	0.108	0.281
Observations	40	40	40	40

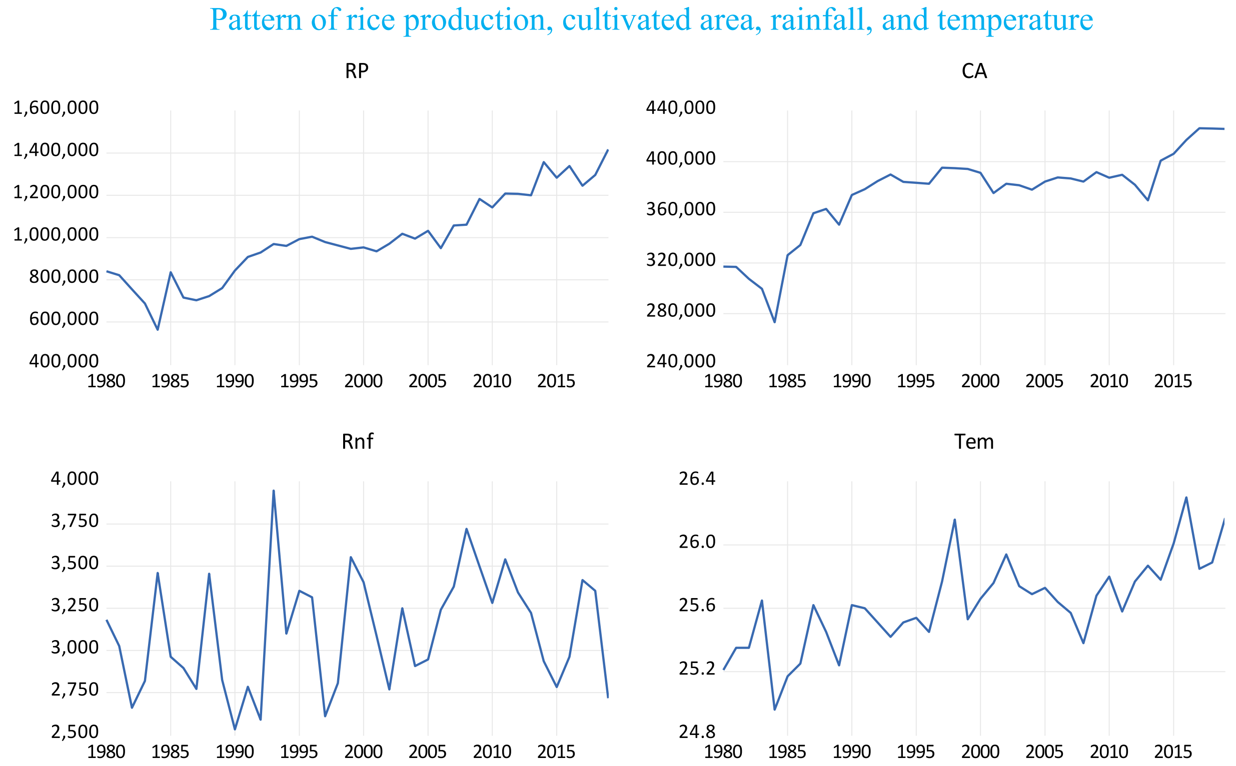

Fig. 1. Trend of the study variables.

OLS parameter estimations unless the variables are co-integrated [21]. Furthermore, the co-integration examination was started by determining the time series' univariate features. The following requirements must be met in order for the co-integration analysis to produce meaningful results: integration of all variables in the similar instruction and stationarity of their linear amalgamations.

With the exception of rainfall, all variables in this study's time series data were non-stationary and at constant values. After that, we ran unit root tests to determine whether all variables were stationary at levels and initial differences. Despite the literature's recommendation of numerous tests for stationarity, we used the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), Dickey-Fuller Generalized Least Squares (DF-GLS), and Zivot and Andrew (Z & A) [68] unit root tests to account for any structural discontinuities in the variables' data. As indicated in Tables 3 and 4, both the level and the initial variance of the natural log of the variables were examined using the unit root test, which showed that all variables were stationary at the initial variation. In general, time series data are prone to volatility due to structural events such as natural disasters (earthquakes), macroeconomic challenges (2008/2009 financial meltdown), or disease outbreaks (COVID-19 pandemic).

Unfavourable events that cause structural change can have an impact on the stability of pointers and variables, and thus must be accommodated to ensure accurate research work. As a result, for the analysis, we utilised both ADF and PP, DF-GLS, and the structural break tests from Zivot and Andrews [68]. While conservative unit root tests focus on the general description of the variable's stationarity, structural break tests concentrate on exposing the year with the structural break that can cause a prolonged or everlasting shock in the economy. The results of traditional unit roots and DF-GLS are shown in Table 3, and there is an assorted order of incorporation indicating the existence of a unit root. Additionally, Table 4, Zivot Andrew test result showed that the variables are stable even when there are structural breakdowns at I(0) and I(1).

Brock et al. [13] pioneered this test (BDS), which uses a correlation integral, to measure frequency. The aim of the BDS investigation is to discover patterns of logical, anticipated non-stationarity in time series that were unfamiliar. The BDS test helps distinguish

Table 3
Results of the unit root testing using P–P, DFGLS, and ADF.

At level				1st difference			
Variables	ADF	DF-GLS	P–P	Variables	ADF	DF-GLS	P–P
LRP	−1.415	−0.780	−0.370	LRP	−3.247**	−5.232***	−9.529***
LCA	−1.510	−0.804	−1.423	LCA	−7.156***	−7.180***	−7.322***
LRNF	−4.973***	−5.040***	−4.912***	LRNF	−5.367***	−7.683***	−16.710***
TEM	−1.307	−0.679	−2.765*	TEM	−7.718***	−6.291***	−21.319***

"(***), (**), and (*) represent 1%, 5% and 10% level of significance, respectively".

Table 4
Structural break unit root test.

Variable	At level			1st difference		
	T-stats	Break-point	Result	T-stats	Break-point	Result
LRP	−4.390*	1990	Stationary	−2.739**	1995	Stationary
LCA	−3.991	1991	Unit root	−3.501*	1992	Unit root
LRNF	−5.804**	1993	Stationary	−5.678*	1993	Stationary
TEM	−5.961**	2004	Stationary	−7.580***	1999	Stationary

Table 5
Non-linearity BDS test statistic.

BDS statistic	Di-2	Di-3	Di-4	Di-5	Di-6
LRP	0.1002***	0.176***	0.237***	0.265***	0.307***
LCA	0.184***	0.314***	0.407***	0.473***	0.523***
LRNF	−0.001*	−0.001	0.005*	0.024**	0.021
TEM	0.028**	0.050***	0.062***	0.027	0.027

"The asterisks (***), (**) and (*) denote the rejection of null hypothesis that the residuals are iid at 1%, 5%, and 10% significance levels respectively".

among both chaotic and non-linear procedures. The test can be used to evaluate a number of other types of non-linearity, even though it was intended to be more effective than linear chaos. The BDS test outcomes are listed in Table 5, and they show that the null hypothesis that the series are linearly dependent is vetoed. Rainfall was the only embedding dimension for which the BDS statistics were not significant, proving that none of the variables were linear. The BDS statistics increased as the embedding dimensions increased, demonstrating the strong non-linearity for large dimensions. After confirming that the model has structural breaks and non-linearity, the NARDL Model coefficients were estimated.

4.3. *Analysis of cointegration*

The Autoregressive distributed lag bound test was employed in this work to identify the presence of co-integration. The notable minimal lag values of the LR, FPE, AIC, and HQ were utilised to create the F-statistics for co-integration using lag 3, as shown in Table 6. Additionally, the vector autoregressive (VAR) model's lag selection approach (see Fig. 2), which depicts a polynomial graph with all dots contained inside a circle, supported the suitability of lag length 3 for judgment and strategy insinuations.

The combined effect of all regressors was estimated using the F-statistics under the Wald test, which showed that there was only one co-integration between the variables. Table 7 shows that the calculated F-statistics value of 4.501 was revealed, which is greater than Narayan's critical value of 4.450 [40]. At the 5% level of consequence, the null hypothesis that there is no co-integration is thus denied. Since Narayan's significant level was developed using stochastic simulations with a sample size based on 40,000 repetitions, it is thought to be superior to Pesaran, a comparison was made between the calculated F-statistics and Nayaran's critical value [41]. Similar to the case of linear cointegration, the results demonstrate that the null hypothesis is invalid. The variables are cointegrated at the 5% significant level, according to the results of the bound test.

4.4. *The evaluation of both long- and short-term scenarios*

Tables 8 and 9 show the long-run elasticity of the various variables on rice production. The ARDL findings demonstrated a favourable and significant long-term and short-run association between cultivated area and rice output. According to the findings, a 1% upsurge in cultivable land will result in an upsurge in rice output of 2.079% over the long term and 1.633% over the short term.

Rainfall and rice output did have a long-term, favourable, and statistically significant link. The results show that a 1% rise in rainfall results in a 0.905% rise in rice yield. The TEM coefficient has no statistically significant effect on rice output.

The dynamics must converge to long-term stability in order for the lagged error correction term (ECMt-1) to be negative as well as statistically significant. The negative coefficient of the ECMt-1 found in this study (see Table 9) suggests that any disequilibrium from

Table 6
Criteria for choosing the VAR lag order.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	32.157	NA	0.012	−1.522	−1.347	−1.461
1	42.470	17.838	0.007	−2.025	−1.807	−1.948
2	46.413	6.607*	0.006	−2.184	−1.923*	−2.092
3	48.011	2.591	0.006*	−2.216*	−1.912	−2.109*

"* denotes lag order is chosen by the criterion, LR: sequentially modified LR test statistic (each test at 5% level), FPE: Final Prediction Error, AIC: Akaike Information Criterion, SC: Schwarz Information Criterion and HQ: Hannan-Quinn Information Criterion".

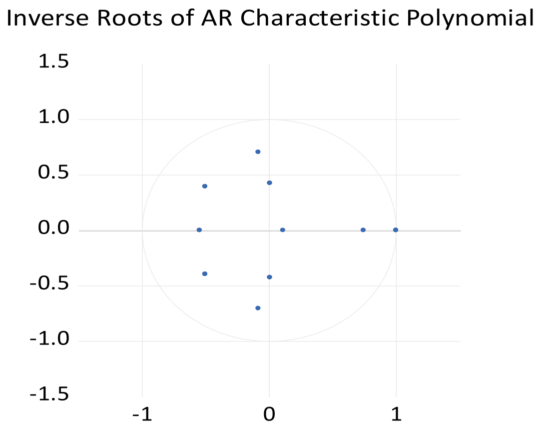

Fig. 2. The polynomial graph's lagged selection criterion under the VAR.

Table 7
Linear and non-linear bounds test results.

Equations	AIC Lag	F-stat.	Outcome
FLRP(LRP|LCA, LRNF, TEM) (Linear)	3	4.501**	Cointegration
FLRP(LRP|LCA$^+$, LCA$^-$,LRNF$^+$, LRNF$^-$,TEM$^+$, TEM$^-$) (Non-Linear)	3	8.381***	Cointegration
Asymptotic critical values, Narayan (2005) I(0)		**I(1)**	
1%	4.394	5.914	
5%	3.178	4.450	
10%	2.638	3.772	

Table 8
Long-term variable prediction from ARDL frameworks.

Variables	Coefficient	Std er	T-stat [Prob]
LCA	2.079***	0.734	2.833[0.008]
LRNF	0.905*	0.505	1.792[0.083]
TEM	0.174	0.208	0.835[0.410]
C	−5.584***	1.758	−3.176[0.003]

Table 9
Short-term variable prediction from ARDL frameworks.

Variables	Coefficient	Std. Error	T-ratio [Prob]
ΔLCA	1.633***	0.216	7.554[0.000]
ΔLRNF	0.099	0.069	1.422[0.166]
ΔC	−6.882***	1.745	−3.942[0.000]
ECM(-1)	−0.279***	0.070	−3.949[0.005]

Table 10
Diagnostic test of ARDL model.

Diagnostic Tests	F-stat	P-value
R-square	0.948	
χ2 Serial correlation	0.331	0.721
Adjusted R square	0.936	
χ2 Normality	0.571	0.751
χ2 Breuch-Pagan- Godfrey test	0.593	0.775
χ2 ARCH	1.160	0.288
χ2 Ramsey RESET	0.070	0.792

previous years can be corrected in 3.58 years at a rate of 27.9%, which is a fair speed of convergence toward long-term balance.

4.5. Tests for structure and diagnostics reliability

The outcomes of the various diagnostic tests run on the models are revealed in Table 10. These diagnostic procedures verified that there were no serial correlation, abnormality, or heteroscedasticity problems with the models. The R^2 score of 95% confirms the diagnostic and structural stability tests' applicability, as well as the model's good fit.

We prioritized the analysis of possible shifts in the estimated models over time due to the importance of stable rice production (LRP) in implementing sound economic and agricultural policy. The CUSUM and CUSUMSQ statistics graphs in Fig. 3a and 3b support the stability of the rice production (LRP) function parameters across the study period and are within the critical bounds.

4.6. Non-linear ARDL model

Table 7 displays that there was no statistically momentous trend at the 1% level, and the derived F-statistic values (8.381) are larger than the upper bound of Narayan's [40] table's critical value (5.914). Alternately, the outcome of the co-integrating equation can be utilised to determine the attendance or absence of a long-term association ECTt-1. This displays that the lagged error correction term (ECTt-1) has a destructive and statistically significant value [43] due to the long-run association among RP, CA+, CA-, RNF+, RNF-, TEM+, and TEM-. As a result of the study's detection of a statistically significant negative value of ECTt-1, all prior years' disequilibrium will be rectified within nearly three years and at a 40% rate, which is considered a respectable connection to long-run stabilization (Table 12).

The long and short runs of the nonlinear ARDL are displayed in Tables 11 and 12, accordingly. When it comes to the association between rice productivity and cultivated area, the NARDL results are favourable and statistically significant, which is similar with the ARDL findings in both the short- and long-term. Regarding the long-run asymmetry between rice production and cultivated area, it was found that positive shocks of CA increased rice production. According to the coefficient estimate, a 1% increase in positive shocks in the planted area results in a 2.39% increase in rice productivity. The short-run coefficient estimates states that a 1% upsurge in adverse shocks in the cultivated area corresponds to a 2.12% decline in rice production.

The estimates for the long-term effects of changes in rainfall, optimistic (RNF+) and destructive (RNF-), on rice output are equivalent to −2.061 and −2.522, respectively. As a result, the influence of negative rainfall is much more pronounced. According to the data, rice production is expected to decline by 2.522% with every 1% decrease in rainfall and upsurge by 2.061% with every 1% upsurge in rainfall. This finding implies that rainfall and rice output in Malaysia have an unbalanced association. Conversely, in the short term, the coefficients for the effects of changes in rainfall that are favourable (RNF+) and negative (RNF-) on rice output are equivalent to 0.223 and −0.525. It implies that 1% changes in rainfall result in increases in rice production of 0.223% and 0.525%, respectively. This outcome is comparable to the ARDL technique.

The estimates for the long-term impacts of temperature optimistic (TEM+) and destructive (TEM-) variations on rice production are equivalent to −2.937 and −2.058, respectively. As a result, the impact of negative temperature is much more substantial impacts on rice output. It directs that a 1% upsurge in positive temperature shocks results in a 2.937% drop in rice production and a 1% rise in negative TEM shocks results in a 2.058% gain in rice production in Malaysia. On the other hand, positive temperature shocks have no short-term impact on rice production. However, negative temperature shocks have a favourable impact on rice output in the short run. It implies that a 1% rise in negative temperature shocks resulted in a 0.237% upsurge in rice output in Malaysia.

The Breusch-Pagan-Godfrey (BPG) heteroscedasticity test and the ARCH test both yielded insignificant probability chi-square values, which is why the null hypothesis of homoscedasticity is rejected, as shown by the diagnostics test results at the bottom of Table 11. The Serial Correlation LM test and the Jarque-Bera test for normalcy were also performed. Both tests yielded statistically negligible probability chi-square values, supporting the model's normality and absence of serial correlation. To assess how robust our conclusions are, the CUSUM and CUSUMsq were used to examine the dynamic stability of our model [14]. The outcomes of CUSUM and CUSUMsq, depicted in Fig. 4a and Fig. 4b, indicate that the overall model remains stable.

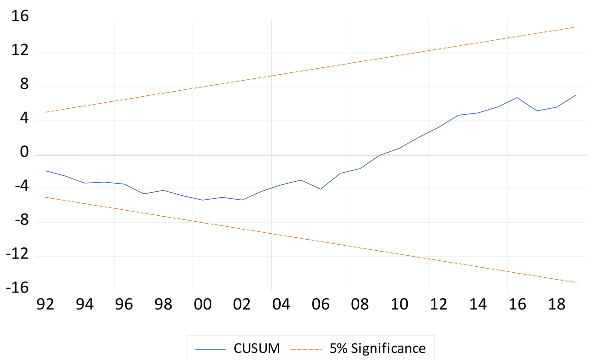

Fig. 3a. The recursive residuals cumulative sum plot.

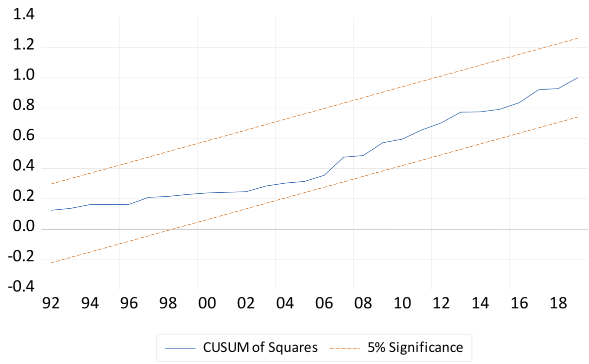

Fig. 3b. Recursive residuals with cumulative sum of squares plot.

Table 11
Long-run NARDL estimates and diagnostic tests.

Regressor	Coef.	Std. error	t-Stats	P-value
LCA_POS	2.390*	1.105	2.162	0.058
LCA_NEG	−14.352**	5.953	−2.411	0.039
LRNF_POS	−2.061*	1.096	−1.880	0.092
LRNF_NEG	−2.522*	1.209	−2.085	0.066
TEM_POS	−2.937**	1.204	−2.439	0.037
TEM_NEG	−2.058*	1.022	−2.013	0.074
C	9.125**		10.836	0.000
Model Statistics Probability				
R^2				0.994
Adjusted R^2				0.977
F-stats				59.477
Probability (F-stats)				0.000
Diagnostic tests				
Test			Test-Statistic	Prob.
LM test			0.380	0.554
Heteroscedasticity test			0.299	0.992
ARCH test (Heteroscedasticity)			0.489	0.489
Normality test			1.128	0.568

Table 12
Short-Run non-linear ARDL Estimates.

Regressor	Coef.	Std. error	t-Stats
D(LCA_POS)	−2.117***	0.446	−4.737
D(LCA_NEG)	−0.514	0.447	−1.077
D(LRNF_POS)	0.223**	0.082	2.700
D(LRNF_NEG)	−0.525***	0.117	−4.450
D(TEM_POS)	−0.036	0.059	−0.621
D(TEM_NEG)	−0.237**	0.086	−2.747
ECM(-1)	−0.403***	0.041	−9.888
C	4.574	0.459	9.953

"***,**, and * show 1%,5% and 10% level of significance".

Finally, using NARDL multipliers for the explanatory (LCA, LRNF, and TEM) variables, Fig. 5 shows the changes made to the new equilibrium equations as a result of the prior destructive and optimistic shocks. The black-scattered and hard black stripes show, respectively, how RP asymmetrically adjusts to destructive and optimistic shocks. The asymmetric pattern and critical boundaries, respectively, are indicated by the thick and narrow, red-dotted lines. Fig. 5 phase patterns support the asymmetric relationship between cultivated area, rainfall, temperature, and rice production in Malaysia.

4.7. The outcome of the asymmetric causality test

Although we have looked at both the long- and short-term effects of regressors on the dependent variable, it is equally crucial to consider the causal association among variables when making policy recommendations. We used the Granger procedure within the VAR [21] causality test. We simply discuss the Granger causality findings between rice production and meteorological variables in

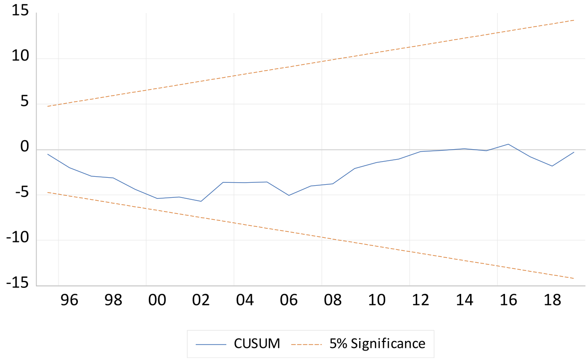

Fig. 4a. The CUSUM of recursive residuals plot.

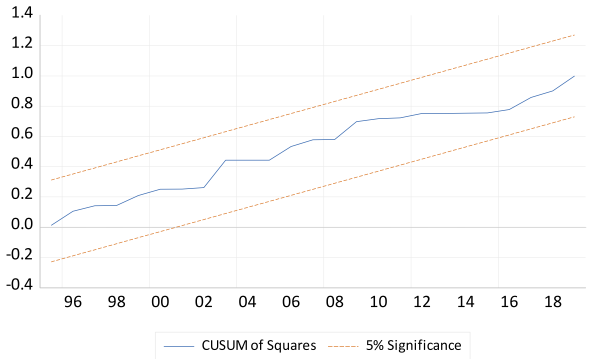

Fig. 4b. The CUSUM of squares of recursive residuals plot.

order to conserve space. The long-term feedback relationship between rice output, cultivable land area, rainfall, and temperature is demonstrated by the long-term causality data in Table 13. There is evidence of unidirectional causation runs from the based model's $LRNF^{+}\rightarrow$ LRP and $LRNF^{-}\rightarrow$ LRP, $LCA^{+}\rightarrow$ LRP, and $LCA^{-}\rightarrow$LRP, and $TEM^{+}\rightarrow$ LRP, and $TEM^{-}\rightarrow$ LRP. The research also discovered a bidirectional link between negative TEM and negative LRNF in this model.

4.8. Robustness analysis

The accuracy of the long-term estimations obtained from the ARDL estimation could be further confirmed by using simultaneous equation estimate techniques as FMOLS, DOLS, and CCR. The FMOLS estimate assumes a single relationship among the variables and then applies a semi-parametric modification to remove the estimating problems caused by the cointegration's long-term relationship with the stochastic challenges. The CCR estimation is comparable to FMOLS, with the exception that it is used to solve cointegration issues instead of stationary data modifications. The inclusion of assorted order integration of variables in the cointegrated framework, as well as the reduction of endogeneity and trivial sample size bias, are the main benefits of the DOLS test [74]. Table 14 displays the outcomes of the FMOLS, DOLS, and CCR. It demonstrates that the findings of long-run ARDL estimate with FMOLS and DOLS have similar signs for LCA and LRNF. Similar to FMOLS, DOLS, and CCR findings, LCA, LRNF, and TEM in non-linear ARDL long-run outcomes are reliable.

5. Discussion and policy implications

It was found that shocks to the cultivated area, both positive and negative, have a optimistic and substantial impact on RP in the long run. On the other hand, positive shocks of cultivated areas have adverse impacts on RP in the short term. This finding is comparable to those made by Pickson, He, & Boateng, [46]; Nasrullah et al. [38], who discovered that the planted area had a considerable impact on RP. In China and Korea, the cultivated area showed a considerable affirmative short-term link with rice yield [38,46]). In India, Somalia, and Pakistan, Kumar et al. [33]; Warsame et al. [64]; Ahsan, Chandio, and Fang [4] revealed that farmed areas had a beneficial impact on cereal crop yield. In both the short and long terms, the area planted in cereal crops significantly and favourably affected Bangladesh's grain production [16]. This implies that cultivated land encourages more production in both the long and short term. However, the cultivated area and rice output in Malaysia are moving in the opposite way during the short term.

This study also discovered that positive rainfall shocks have a negative influence on RP and destructive rainfall shocks have a

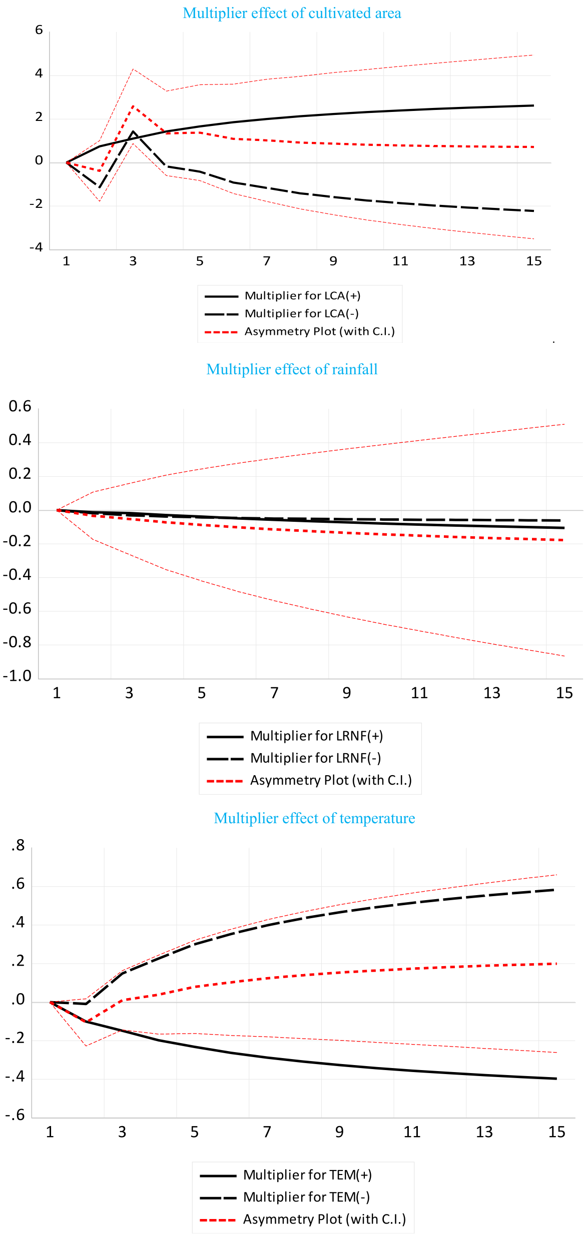

Fig. 5. The multipliers for LCA, LRNF and TEM.

beneficial impact on RP in the long run. The productivity of wheat and rice crops has been found to be destructively impacted by seasonal RNF, suggesting that excessive rainfall in India has been unproductive [12,32]. Mitra and Rao [36] asserts that a lot of rain can be detrimental to crop production. Rainfall has a detrimental effect on South Korea's ability to produce rice, according to research by Nasrullah et al. [38]. With long-term positive shocks, the outcome is comparable. However, in the short run, both optimistic and destructive RNF shocks have a considerable positive impact on rice production. This result is consistent with Abbas et al. [2]; and Jan et al. [28]. They discovered that Pakistan's rice production is significantly and favourably impacted by rainfall. In their exploration of the impact of meteorological variables on grain production in Tunisia, Attiaoui and Boufateh [7] found that rainfall significantly increases cereal yield. Rainfall in Somalia upsurges agricultural production in the long term but reduces it in the shorter term [64].

The study investigates how temperature affects rice production. According to the study, long-term positive temperature shocks have a detrimental and considerable impact on rice output. However, negative temperature shocks have a beneficial and statistically momentous impact on rice output in both the short and long run. This outcome is consistence with Abbas and Mayo [1], Rezaei et al. [50], and Teixeira et al. [59]. They came to the conclusion that the output of rice might be negatively impacted by global warming.

According to Rayamajhee et al. [49], a 1 °C upsurge in the average summertime TEM causes a 4183 kg decrease in rice yield in

Table 13
Granger causality test results.

Causality Direction	F-statistics	P-value
$LRNF^{+} \rightarrow LRP$	4.386**	0.021
$LRP \rightarrow LRNF^{+}$	1.02430	0.371
$LRNF^{-} \rightarrow LRP$	3.107*	0.058
$LRP \rightarrow LRNF^{-}$	0.239	0.788
$LCA^{+} \rightarrow LRP$	3.945**	0.029
$LRP \rightarrow LCA^{+}$	2.01342	0.150
$LCA^{-} \rightarrow LRP$	19.476***	0.000
$LRP \rightarrow LCA^{-}$	2.087	0.141
$TEM^{+} \rightarrow LRP$	6.265***	0.005
$LRP \rightarrow TEM^{+}$	1.636	0.210
$TEM^{-} \rightarrow LRP$	10.082***	0.000
$LRP \rightarrow TEM^{-}$	0.524	0.596
$TEM^{+} \rightarrow LRNF^{-}$	4.194**	0.024
$LRNF^{-} \rightarrow TEM^{+}$	2.060	0.144
$TEM^{-} \rightarrow LRNF^{-}$	2.960*	0.066
LRNF-→TEM-	8.733***	0.000

"***,**, and * show 1%,5% and 10% level of significance".

Table 14
FMOLS, DOLS, and CCR estimation results.

Method: FMOLS			
Regressor	Coef.	Std. error	t-stats
LCA	0.970**	0.418	2.321
LRNF	0.601**	0.265	2.269
TEM	10.672***	3.793	2.813
C	−38.112***	9.906	−3.847
Method: DOLS			
LCA	2.581***	0.729	3.537
LRNF	1.684***	0.508	3.313
TEM	0.054	0.225	0.241
C	−34.327***	6.754	−5.081
Method: CRR			
LCA	0.713	0.499	1.429
LRNF	0.783**	0.365	2.143
TEM	13.135**	4.919	2.670
C	−44.272***	12.521	−3.535

Nepal. Extreme heat in Malaysia hinders the growth of rice [8,23]. It was discovered by Tan et al. [57] that the maximum TEM had a destructive impact on yield during the off-season, the minimum TEM had a favourable impact during both crop seasons.

As a result, this study provides useful information for immediate practical forecasts, policy design, and policy implementation in relation to predicted CC adaptation and rice production planning at the regional level. The Malaysian government might use these findings to support effective rice production management, which would address the global issue of food stability as one of the SDGs. The outcomes of this study could be critical for legislators' planning and strategy in adopting proper environmental regulations and current technologies for precise climate forecasting. In order to combat the already noticeable effects of CC on agriculture, policymakers must implement comprehensive adaptation and mitigation strategies. This will allow Malaysia to resume vigorous and stable production of rice. Improved irrigation infrastructure and the introduction of high-temperature stress-tolerant rice cultivars, as well as improved crop disease and pest management, are examples of such adaptation measures. As a result, Malaysia must reconsider its climate change adaptation methods, taking into account the following factors: To begin, meteorologists, policymakers, and researchers must devise effective techniques and synthesis complete policies to solve climate change's problems. This will guarantee that the nation's levels of self-sufficiency (SSL) and nutrition security increase over time. Secondly, the country should prioritise improving farmers' ability to adapt to the effects of climatic change on their agricultural activity. Thirdly, the government of Malaysia should use agricultural research to develop policy-based changes.

Furthermore, Malaysia has not yet formulated a nationwide strategy for adjusting agriculture to climate change. Finally, certain methods and programs under the current policy need to be revised. For instance, the concerned authority should ensure the nation's SSL as a security measure to combat the future food crisis. In conclusion, farm-level adaptations are critical for improving farmers' adaptive skills and ensuring agricultural sustainability in the long run.

6. Conclusions

Malaysia's rice production would decline drastically due to CC [8,23,57]. Because rice is Malaysia's main staple food, research on the effects of CC on rice yield is essential. However, production is declining year by year and is insufficient to meet national demand. Regional ranchers are under pressure due to this decline in rice production, which also grabs the attention of government officials. Hence, utilising yearly data from 1980 to 2019, the primary goal of the study is to observe the symmetric and asymmetric association among rice yield, cultivated area, rainfall, and temperature in Malaysia. Climate factors have a significant influence on rice output, according to the key findings. The ARDL empirical result infers that in Malaysia, there is a linear dynamic association among rainfall and rice output. On the other hand, the NARDL outcome exhibits that there is a considerable long run and dynamic asymmetry connotation between meteorological variables and rice production in Malaysia. Rice production in Malaysia has been impacted by both the good and negative consequences of climate change to varying degrees. In contrast, the basic ARDL approach is inefficient in determining how asymmetries in climate change would affect rice yield in the medium and long term and could produce biased and erroneous results. Asymmetric long-run results show that optimistic and destructive annual mean TEM and RNF have an adverse and optimistic impact on RP, correspondingly. Additionally, both the optimistic and destructive effects of rainfall have a substantial favourable effect on RP in the short term. On the other hand, the negative and optimistic components of temperature have a large adverse and optimistic impact on rice output in Malaysia. In the long run, the optimistic and negative components of cultivated area have a favourable impact on Malaysia's RP. Furthermore, in the short run, the optimistic and destructive components of cultivation have a considerable destructive and optimistic impact on RP. However, this study has some limitations. This study only focus at rice production, cultivated area, temperature, and rainfall in one country. We are unable to consider those variables due to a lack of data on solar radiation and air temperature. However, future research could focus on cross-country analyses and additional variables.

Author contribution statement

Qing Zhang: Conceived and designed the experiments; Analyzed and interpreted the data; Wrote the paper.

Rulia Akhtar: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Wrote the paper.

Abu Naser Mohammad Saif: Contributed reagents, materials, analysis tools or data; Wrote the paper.

Hamida Akhter: Analyzed and interpreted the data.

Dalowar Hossan: S. M. Ashraful Alam: Md. Fakhrudoza Bari: Contributed reagents, materials, analysis tools or data.

Data availability statement

Data associated with this study has been deposited at the [https://data.worldbank.org, https://www.dosm.gov.my/v1].

Additional information

No additional information is available for this paper.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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